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Determination of the reduction coefficients in a continuous finishing group of stands in a hot rolling mill using artificial neural network

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Abstract. There are many problems when creating digital doubles. One of which is the definition of the source data: in this case, the definition of private reductions (coefficient ratios) in a continuous finishing group of stands of the broadband hot rolling mill 2000 of PJSC Magnitogorsk Iron and Steel Work. Algorithms were developed to calculate the thickness of the breakdown bar, the number of stands involved, power required for rolling and coefficient ratios to solve this problem. The algorithms are based on well-known solutions (the Imai method) using neural networks. The training of neural networks was conducted on a sample collected for the period from 01.01.2017 to 01.01.2019 work of the mill in the PyTorch library of the interpreted programming language Python. The average error ε_{ME} of the calculation of coefficient ratios (according to the developed algorithms with neural networks) does not exceed 8.9% and the standard deviation σ does not exceed 0.074.

1. Introduction

Broadband hot rolling mills are one of the main means of production of hot rolled products. So, for example, the broadband hot rolling mill (BHRM) 2000 of PJSC Magnitogorsk Iron and Steel Work in 2019 produced 6 million tons of hot rolled strips. On the example of this mill, the following trends in production are observed: increased productivity; increasing requirements for the quality of rolled products (in geometry and mechanical properties), thinning of rolled products, the emergence of new high-strength steel grades, increasing the variety of assortment (for steel grades and strip geometry) in one rolling company (rolling between work roll changes in the finishing group of the mill stands)These trends lead to the need for innovations in production. So, recently the direction (since 2000) for the creation of digital twin of production processes has been developing [1]. So, in relation to BHRM 2000, this technology allows you to simulate a mill's production line in a virtual environment, as well as run a preliminary production optimization. Due to this, the sources of errors or failures can be identified and eliminated even before the actual operation. This significantly saves time and lays the foundation for individualized mass production, since complex production routes can be quickly calculated, tested and programmed with a minimum of cost and effort.

However, with this ‘virtual prototyping’ many problems arise, one of which is the definition of the source data for modeling physical processes. So, one of these problems is the determination of reduction coefficients in a continuous finishing group of BHRM 2000 stands.

The reduction coefficients in finishing stands are usually determined by loading the main drives (Imai method [2]), while determining the necessary coefficients using statistical methods [3–5]. This article proposes a method for selecting reduction coefficients using artificial neural network models. Artificial neural networks have established themselves, especially in the last decade, as a convenient tool for forecasting and data processing [6, 7]. In particular, for rolling production, artificial neural network models are used to predict power parameters [8, 9], thermal state of the strip and work rolls [10, 11], wear of the work rolls [12], strip profile [13], mechanical properties [14] and etc.

2. Artificial neural networks

2.1. Methods

In the paper for data prediction: (number of stands involved, breakdown bar thickness (strip thickness after leaving the roughing group of stands), reduction coefficients), generalized regression neural networks are used. Learning and building a neural network is implemented using the PyTorch library of the interpreted programming language Python.

The training of neural networks was carried out on the data obtained from the databases of technological parameters of BHRM 2000 of PJSC Magnitogorsk Iron And Steel Work. The training was conducted on a sample collected for the period from 01.01.2017 to 01.01.2019 work of the mill.

2.2. Determination of thickness of breakdown bar

Algorithms of papers [3–5] were taken as the basis for determining the reduction coefficients. According to these algorithms, to determine the reduction coefficients, it is first necessary to determine the thickness of the intermediate roll h_p and the number of N_{st} stands involved in the finishing group.

The paper proposes to determine the coefficient of the total compression η_{sum} using a trained neural network. To determine the thickness of the breakdown bar h_b, an algorithm was developed, shown in Figure 1.

The structure of the neural network is a multilayer perceptron, consisting of an input layer (4 neurons), one hidden layer (containing 9 neurons) and an output layer containing 2 neurons. The 'ReLu' function was used as an activation function (Table 1).

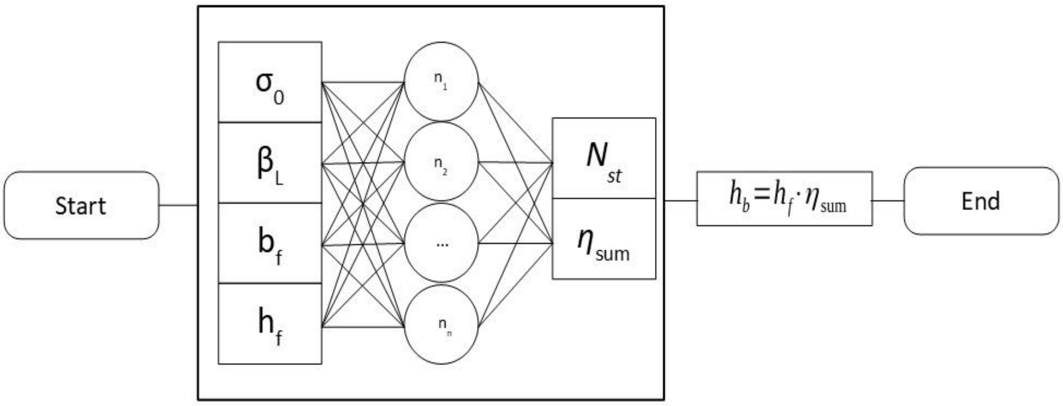

Figure 1. The algorithm for determining the thickness of breakdown bar h_p, based on the artificial neural network: σ_o–basic deformation resistance, MPa (for the condition: rate of strain $\xi = 1$ c^{-1}, reduction coefficient $\varepsilon = 0.1$ and temperature $t = 1000$°C); $\beta_L = b_s/L_{w.r.}$ – coefficient of usage of the work roll barrel, where b_s – strip width, mm; $L_{\text{w.r.}}$ – work roll barrel length, mm, b_f – strip width at the exit from the finishing group, mm; h_f – strip thickness at the exit from the finishing group, mm; N_{st} – the number of stands involved in the rolling process.

2.3. Determination of the reduction coefficients

To determine reduction coefficients in the finishing groups of sheet mills of hot rolling, it is proposed to modify the Imai method [2], developed in the works of M Rumyantsev [3–5].

Table 1. Artificial neural network parameters.

Neural network architecture	Input layer: 4 neurons Output layer: 2 neurons Hidden layer: 11 neurons
Activation function	Relu
Training mode	'Step by step training'
The degree of recognition of the training set, %	98.1
The degree of recognition of the test set, %	92.5
Mean absolute percentage error ε_{MAPE}, %	4.7
Max absolute error, %	19.1

The basic expression Imai (1) is used to calculate the reduction coefficients.

$$h_{1i} = \frac{h_p h_к}{\sqrt[im]{\beta_{Wi} h_p^{im} + (1-\beta_{Wi}) h_к^{im}}}, \tag{1}$$

where h_{1i} – the work roll nip in the i-th stand; $im = 0.30 + \frac{0.21}{h_к}$ – Imai coefficient; $\beta_{Wi} = \sum_{j=1}^{j=i} W_j / \sum_{i=1}^{i=N_F} W_i$ – power factors of the main drives; W_i – power required for rolling in the i-th stand.

Prediction of reduction coefficients in the finishing group of stands of hot-rolled sheet mills is realized using the constructed neural network, the structure of which is shown in Figure 2.

The artificial neural network included in the algorithm for determining reductions in the finishing group of stands consists of an input layer (5 neurons), one hidden layer (containing 11 neurons) and an output layer containing 1 neuron (Table 2).

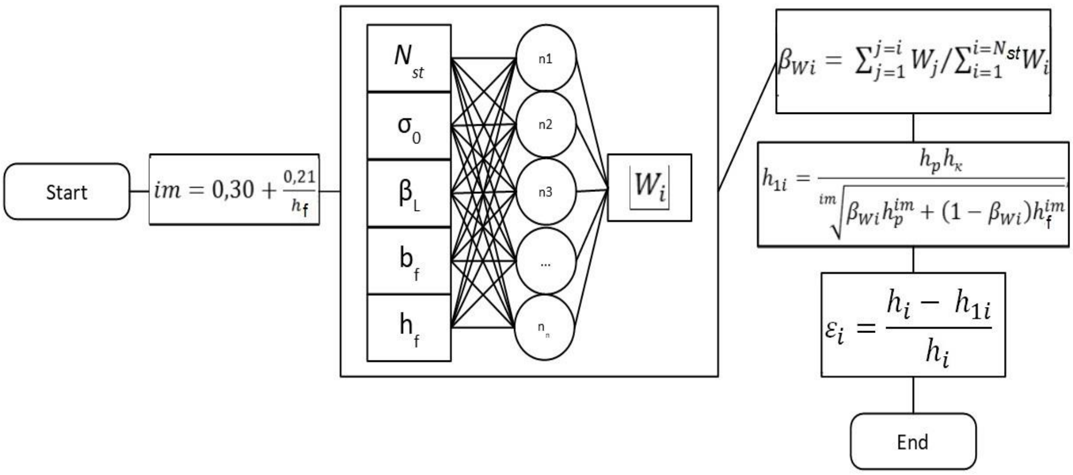

Figure 2. The algorithm for determining the reduction coefficients in the finishing continuous stands of the hot rolling mill: σ_0 – basic deformation resistance, MPa (for the condition: rate of strain $\Xi = 1$ c^{-1}, reduction coefficient $\varepsilon = 0.1$ and temperature $t = 1000$°C); h_{1i} the work roll nip in the i-th stand; im – Imai coefficient; β_{Wi} – power factors of the main drives; W_i – power required for rolling in the i-th stand.

3. Conclusion

Thus, in the course of the study, an algorithm was obtained based on neural network modeling, which allows one to select and determine reduction coefficients at BHRM 2000 of PJSC Magnitogorsk Iron And Steel Work.

Table 2. Artificial neural network parameters.

Neural network architecture	Input layer: 8 neurons Output layer: 1 neuron Hidden layer: 11 neurons
Activation function	Relu
Training mode	'Step by step training'
The degree of recognition of the training set, %	96.1
The degree of recognition of the test set, %	91.5
Mean absolute percentage error ε_{MAPE}, %	6.3
Max absolute error, %	12.4

The mean absolute percentage error ε_{MARE}, the mean error ε_{ME} and the standard deviation σ of the calculations of the developed algorithm do not exceed 0.053, 8.9% и0.074, respectively (Table 3).

Table 3. Errors in the calculation of reduction coefficients in the finishing group of stands BHRM 2000.

Stand	Mean error ε_{ME}	Mean absolute percentage error ε_{MAPE}, %	Standard deviation σ
7	0.053	6.3	0.074
8	0.021	4.9	0.038
9	0.028	7.1	0.046
10	0.034	8.9	0.06
11	0.014	7.7	0.025
12	0.016	5.6	0.035
13	0.016	4.7	0.028

Also, it is possible to adapt these algorithms for other hot rolling mills if there is a previously prepared data set for training using selected hyperparameters when training a neural network.

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